ESTIMATING WINTERTIME BATTERY TEMPERATURE IN STAND-ALONE PHOTOVOLTAIC SYSTEMS WITH INSULATED BATTERY ENCLOSURES

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ABSTRACT

Storage battery performance is strongly related to temperature: when cold, a battery's capacity, efficiency, and ability to accept charge decline. In cold climates, the lead-acid batteries commonly used in remote stand-alone photovoltaic (PV) systems typically operate at low temperatures during the winter. In order to ensure that the system functions reliably, the battery must be sized to accommodate poor winter performance.

Designers and installers generally use simple computerized algorithms and simulations to size stand-alone photovoltaic systems. While most of these softwares contain reasonably sophisticated models for calculating insolation, module temperature, module output, controller operation, and battery function, very few incorporate any reasonable model for battery temperature. Many assume that the battery will be at ambient temperature, at a specified minimum temperature, or at the average temperature over the day. In certain cases, these assumptions are sufficient. With larger battery banks and insulated enclosures, however, they are largely inadequate. It is impossible that these software can accurately model system performance in these cases; in spite of this, sizing and simulation software often include estimates of loss-of-load probability to several significant figures.

Modelling battery temperature is relatively simple. Solution of a simple ordinary differential equation yields a model for battery temperature requiring as parameters the thermal conductivity of the enclosure wall, the enclosure shape and size, the battery mass, and the ambient air temperature. This model is reasonably accurate; higher accuracy can be obtained by accounting for the inefficiency of the battery, which results in heat dissipation within the enclosure. In addition, the model can be adapted for use with phase change materials (PCM), which can establish a temperature "floor", below which the battery temperature will not drop.

This model has been validated for several sites in the Calgary area. The sites were monitored for a period of one year; the model was found to be highly accurate during the winter. The model was less accurate during the summer, probably due to solar heating of the exterior of the enclosure. This experimental validation also demonstrated the technical feasibility of using water as a phase change material to moderate battery temperature.

The implications of the model are explored in two ways: first, the model is used to examine the performance of various enclosures, with and without insulation and phase change materials, and second, the paper demonstrates the importance of incorporating such a model into simulation and sizing software.

1. INTRODUCTION

Much attention has been given to the detrimental effects of high temperatures on the lifetime of lead-acid batteries, as this is a common and expensive problem in the hot climates where most PV systems are installed. In contrast, the cold-climate performance of these batteries has been the focus of much less study. While it is well known that lead-acid batteries perform poorly when cold, the implications of this for system design and sizing have not

been fully explored. As a result, there exist few simulation and sizing tools capable of truly modelling and optimizing stand-alone PV systems designed for cold climates.

Batteries are electrochemical devices, and as such, their performance is closely tied to their operating temperature. There are two principal concerns:

1) At hot temperatures (i.e., above 30° C), corrosion may lead to premature battery failure.
2) At cold temperatures (i.e., below –5° C), discharge capacity, efficiency, and charge acceptance are reduced, and the battery may freeze.

For simulation, these two concerns require fundamentally different approaches.

The effects of high temperatures can often be neglected. A program that models only the operation of a system, e.g., a sizing software, can safely ignore high battery temperatures, which detrimentally affect lifetime but actually improve battery efficiency, capacity, and charge efficiency. A program which must additionally assess battery lifetime will need some sort of estimate of the typical battery operating temperature, but this estimate can be quite rough. In hot climates, therefore, an accurate method for predicting battery temperature is not required.

In cold climates, accurate prediction of battery temperature is critical. Photovoltaic systems will fail when the battery is no longer able to furnish power to the load. The ability of the battery to provide current is directly related to its temperature. Therefore, assessing whether a PV system will fail requires an accurate estimate of battery temperature.

Any attempt to model batteries at cold temperatures requires as input an estimate of battery temperature, yet this has been ignored in most existing software packages. This calls into question the validity of any simulation of a PV stand-alone system for a cold climate. The ramifications of this shortcoming are several:

1) Some systems, designed using simulation, fail.
2) Other systems, also designed using simulation, do not fail only because the designer applies a safety margin to the array size or battery capacity or both. While the resulting system is reliable, it is probably oversized, and thus costs more than it needs to.
3) Insulated battery enclosures, which can cost-effectively reduce problems due to cold temperatures[1], are not widely used, since existing simulations and sizing methods are not sufficiently accurate to demonstrate their advantages.

2. A SIMPLE MODEL

In most stand-alone PV systems, the batteries will be placed in an enclosure. The enclosure will also contain air and, in some cases, a mass of phase change material (PCM), which will moderate temperature fluctuations inside the enclosure through its specific heat and latent heat of fusion. Assume that:

1) The interior of the enclosure is isothermal and at a temperature, T.
2) The temperature of the exterior of the enclosure is equal to the ambient air temperature, T_{amb}.
3) Heat transfer between the interior and the exterior of the enclosure occurs only by conduction across a wall of thickness L having a thermal conductivity of k per unit of wall thickness.
4) The thermal mass of the air is negligible in comparison with that of the other contents of the enclosure.

Then the thermal state of the interior of the enclosure can be completely characterized by two variables, T and f, the fraction of the mass of the PCM in its liquid state. At temperatures above and below the freezing point of the PCM, T_{pcm}, f will be 1 and 0, respectively. For values of f between 1 and 0, T will equal T_{pcm}. Thus there are two cases that must be considered: when T is equal to T_{pcm} and when it is not.

Consider the case when T is not equal to T_{pcm}, i.e., when the PCM is either entirely liquid or entirely solid. Ignoring energy stored in chemical form, an energy balance dictates that the sum of heat conducted into the enclosure across the wall, Q, and the heat generated within the enclosure by battery inefficiencies during charge and discharge, E, must equal the change in specific heat content of the batteries and PCM:

$$Q + E = \left(c_{p,pcm} m_{pcm} + c_{p,b} m_b\right)\left(T - T_0\right)$$

where T_0 is the initial T, c_p is specific heat capacity, m is mass, and the subscripts pcm and b refer to the PCM and the battery respectively. Taking the derivative with respect to time, t, and rearranging yields:

$$\frac{dQ}{dt} = \left(c_{p,pcm} m_{pcm} + c_{p,b} m_b\right)\frac{dT}{dt} - P$$

where P is the average rate of heat generation due to battery inefficiencies.

The constitutive equation for this system relates heat conduction through the wall of the enclosure to the thermal gradient, i.e., Fourier's law:

$$\frac{dQ}{dt} = -\frac{kA}{L}\left(T - T_{amb}\right)$$

where A is the area of the wall.

These two equations can be combined, yielding an ordinary differential equation [2]:

$$T = -\frac{L\left(c_{p,pcm} m_{pcm} + c_{p,b} m_b\right)}{kA}\frac{dT}{dt} + \frac{PL}{kA} + T_{amb}$$

It can be verified that the solution for this equation, with the initial condition of $T=T_0$ at $t=0$, is:

$$T = \left(T_0 - T_{amb} - \frac{PL}{kA}\right)e^{\frac{-t}{\tau}} + T_{amb} + \frac{PL}{kA}$$

where

$$\tau = \frac{L\left(c_{p,pcm} m_{pcm} + c_{p,b} m_b\right)}{kA}.$$

Although a spherical shape would minimize heat losses, which is clearly desirable in cold climates, practical considerations dictate that most enclosures will be boxlike (i.e., rectangular parallelepipeds). The area of the wall for such an enclosure can be approximated by[3]:

$$A = 2(lw + wh + lh) + 2.16L(l + w + h) + 1.2L^2$$

where l, w, and h are the length, width, and height of the internal volume of the enclosure. This relation accounts for the extra wall thickness encountered by that heat passing through the edges and corners of the enclosure.

Now consider the case when T is equal to T_{pcm}. In an elapsed time of Δt, the liquid fraction, f, will be altered by heat flow across the wall of the enclosure and generation of heat within the enclosure by the battery:

$$f_{t+\Delta t} = f_t + \left(\frac{kA(T_{amb} - T_{pcm})}{L} + P \right) \frac{\Delta t}{m_{pcm} H}$$

where H is the latent heat of fusion of the PCM. Note that $f_{t+\Delta t}$, and therefore Δt, are constrained by $0 \le f \le 1$.

In the above P has been assigned to the rate of heat generation by the batteries due to inefficiencies during charge or discharge. While this is the most obvious application of P, it can be used more generally to represent the rate at which heat enters the enclosure by any means unrelated to the thermal gradient between the exterior and the interior of the enclosure. For example, P could include the power dissipated by a resistor within the enclosure.

3. APPLICATION AND VALIDATION OF MODEL

This model has been validated against monitored data from two systems in the Calgary area. These systems consisted of a nominally 155 Watt PV array, an on/off charge controller, and six Global Yuasa 85T15 tubular flooded batteries (each nominally 2 V, 745 AH at C/20 rate). The load was 5.5 W. At one site, the batteries were placed in a Soltek Powerhouse enclosure, i.e., an aluminium box insulated with extruded polystyrene (thermal conductivity of 0.029 $Wm^{-2}K^{-1}$). The insulation thickness varied: two walls had 0.14 m; two walls, 0.15 m; the floor, 0.12 m; and the lid, 0.15 m. The enclosure's interior dimensions were 0.63 m by 0.48 m by 0.32 m. At the other site, the batteries were placed in a Soltek Minus 40 enclosure, i.e., an aluminium box with 0.15 m of polyisocyanurate insulation (0.022 $Wm^{-2}K^{-1}$), containing 215 litres of water (PCM) and having a cubic interior of dimension 0.74 m.

Data were collected from November 9, 1995, to November 27, 1996, with approximately one week of data missing from late June. Load current, battery current, array voltage, battery voltage, battery temperature and ambient air temperature were measured each minute. Readings were integrated and recorded hourly.

The model was applied to the two sites. Parameters are described in Table 1. Two variations of the model were tried: in the first, P was set to zero (i.e., the batteries were assumed 100 % efficient), and in the second, P was calculated assuming the batteries had an efficiency on charge, η_{ch}, of 0.82, and an efficiency on discharge, η_{dis}, of 0.97. These values were selected because 1) they result in a roundtrip efficiency of 80%, which is reasonable for a cool battery, 2) the charge reaction is exothermic and the discharge reaction endothermic, suggesting that the heat liberated during discharge would be much less than that liberated during charge, and 3) past applications of the model have suggested these as good estimates of the parameters. Efficiency is assumed independent of battery temperature and state-of-charge, and all inefficiencies are assumed to generate heat.

Parameter	Site with Powerhouse Encl.	Site with Minus 40 Encl.
H	--	334 $kJkg^{-1}$
$c_{p,pcm}$	--	4.2 $kJkg^{-1}K^{-1}$
$c_{p,b}$	1.0 $kJkg^{-1}K^{-1}$	1.0 $kJkg^{-1}K^{-1}$
m_{pcm}	0 kg	215 kg
m_b	207 kg	207 kg
k	0.029 $Wm^{-2}K^{-1}$	0.022 $Wm^{-2}K^{-1}$
A	1.79 m^2	4.03 m^2
L	0.145 m	0.15 m

Table 1 Parameters

Calculating P was complicated because an average reading of the battery current for the hour masks variation between charge and discharge within the hour. During certain hours, when the battery was nearly fully charged, the controller would regulate, i.e., cycle between charge and discharge. Since a shunt controller was used, it was assumed that regulation occurred in those hours when 1) the current from the array, I_{arr}, was greater than zero, and 2), the battery voltage, V_b, exceeded the array voltage, V_{arr}. The fraction of the hour spent with the array shunted, f_{sh}, was estimated using the ratio of array voltage to battery voltage-- the closer this was to one, the less time spent with the array shunted:

$$f_{sh} = 1 - \frac{V_{arr}}{V_b}$$

For those hours with regulation, P was approximated using the current to the load, I_{load}, and the current to the battery, I_b:

$$P = V_b(I_b + I_{load} f_{sh})(1 - \eta_{ch}) + V_b I_{load} f_{sh} \left(\frac{1}{\eta_{dis}} - 1 \right)$$

For those hours without regulation, it was assumed that the battery current remained constant, and P was estimated by:

$$P = \begin{cases} V_b I_b (1 - \eta_{ch}) & I_b > 0 \\ V_b I_b \left(1 - \dfrac{1}{\eta_{dis}} \right) & I_b < 0 \end{cases}$$

The model needed to be supplied with initial conditions for the first hour and the hour following the missing data in June. For the first hour, f was set to 1 and the temperature set to the monitored battery temperature. For the hour following the break in data, the f from the hour prior to the

break was adjusted to reflect thawing that occurred during the break, as based on average thaw rates prior to and following the break. At the site without PCM, the temperature following the break was set to the monitored battery temperature plus the error in the modelled battery temperature for the hour prior to the break.

4. RESULTS

Results are shown in Fig. 1 and 2 for the Powerhouse enclosure and Fig. 3 for the Minus 40 enclosure. The mean bias error (MBE) and error with the maximum magnitude are shown in Tables 2 and 3; in general, the magnitude of the root-mean-squared error (RMSE) differed little from that of the mean bias error and has not been given. Table 4 lists the monitored and predicted dates of the onset of freezing and the completion of thawing of the water in the Minus 40 enclosure.

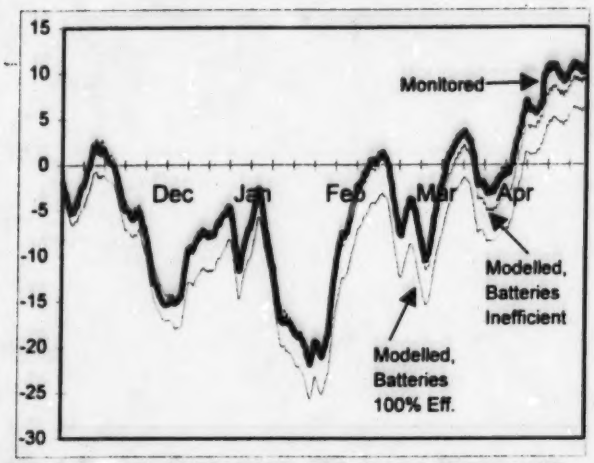

Fig. 1 Battery Temperature (°C) during Winter with Powerhouse Enclosure: Note that the trace for the model accounting for battery inefficiencies often lies underneath the trace for monitored data

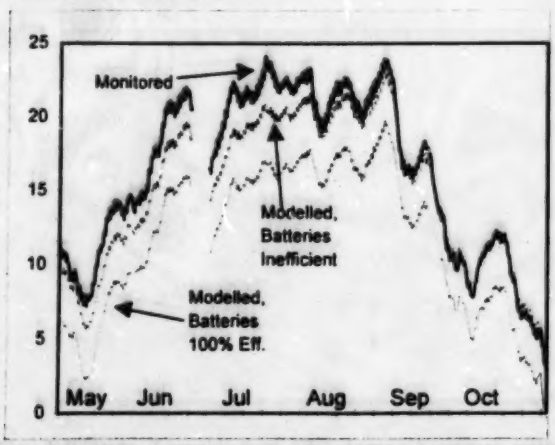

Fig. 2 Battery Temperature (°C) during Summer with Powerhouse Enclosure

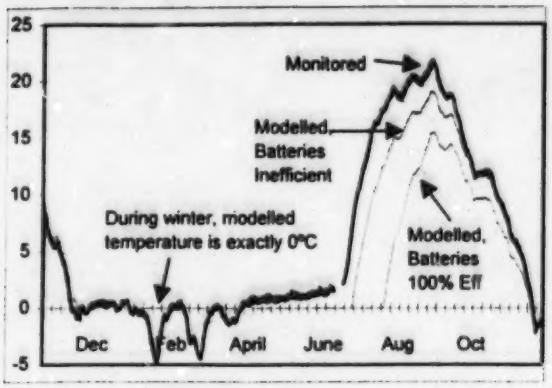

Fig. 3 Battery Temperature (°C) with Minus 40 Enclosure

Clearly the model is much more accurate when the heat generated during charging is included. Simply changing the insulation thickness or thermal conductivity could not significantly improve the accuracy of the model which assumes 100% battery efficiency, since this would reduce variation in the modelled battery temperature, but not correct its bias.

	Batt. 100% Eff		Batteries Ineff.	
	MBE	Max Err	MBE	Max Err
Nov	-2.3	-3.3	0.3	-0.4
Dec	-2.8	-4.0	0.6	1.9
Jan	-3.2	-4.1	0.2	1.0
Feb	-4.7	-5.3	-0.7	-1.4
Mar	-5.6	-6.4	-1.7	-2.5
Apr	-5.4	-6.7	-2.0	-3.1
May	-5.4	-6.3	-2.1	-3.1
June	-5.9	-6.5	-2.4	-3.0
July	-6.0	-7.0	-2.3	-3.4
Aug	-4.4	-5.5	-0.9	-2.1
Sept	-3.3	-4.6	-0.3	-1.5
Oct	-3.2	-3.9	0.2	-0.5
Nov	-2.5	-4.4	0.6	1.3

Table 2 Error of Model (°C) at Site with Powerhouse Enclosure

	Batt. 100% Eff		Batteries Ineff.	
	MBE	Max Err	MBE	Max Err
Nov	-0.2	-0.8	0.7	1.4
Dec	0.0	1.1	0.1	1.4
Jan	0.3	3.2	0.3	3.2
Feb	1.4	4.9	1.4	4.9
Mar	1.7	4.5	1.7	4.5
Apr	-0.2	1.5	-0.2	1.5
May	-0.9	-1.5	-0.9	-1.5
June	-1.6	-4.3	-1.6	-4.3
July	-13.2	-17.5	-5.6	-7.1
Aug	-9.4	-14.8	-3.1	-4.8
Sept	-4.3	-6.5	-1.6	-2.9
Oct	-2.2	-3.0	-0.2	-1.0
Nov	-0.5	-2.1	0.8	2.2

Table 3 Error of Model (°C) at Site with Minus 40 Enclosure

	Monitored	Model: Batt. 100% Eff	Model: Batt. Ineff
Freeze Starts	Dec. 1, 1995	Dec. 1, 1995	Dec. 4, 1995
Full Thaw	June 29, 1996	July 27, 1996	July 3, 1996
Freeze Starts	Nov. 18, 1996	Nov. 17, 1996	Nov. 19, 1996

Table 4 Dates of Freeze and Thaw of PCM

The model appears to be more accurate during winter than summer. It seems unlikely that this is due to parameters used in the model or the way P is calculated: this would require more heat generation within the enclosure during summer, which would imply lower battery efficiency. Since the battery is warmer during summer than winter, and the state-of-charge of the battery is high year-round, this drop in efficiency is improbable. The error seems poorly correlated with ambient or battery temperature: for example, the error is larger in April than August, but August is hotter than April. One reasonable hypothesis for the error is that summer sunshine is heating the exterior of the enclosure, and thus violating the assumption that the exterior of the enclosure is equal to the ambient air temperature. In support of this, the error seems to peak on the summer solstice, although it is skewed more towards spring than autumn.

The significant discrepancies between the measured and the monitored battery temperature during winter in the Minus 40 enclosure are related to the way that water freezes and the assumption that the interior of the enclosure is isothermal. Water freezes from the top down; by late January, when the largest discrepancy occurs, a half-meter thick layer of ice separates the remaining liquid water from the top of the enclosure, where temperature is measured. This layer of ice will permit a temperature gradient within the enclosure. The gradient is most significant during times of rapid heat loss or gain, i.e., when the ambient temperature is very much above or below the freezing point of water.

The large error in the predicted battery temperature that occurs during July and August with the Minus 40 enclosure results from inaccurate prediction of the date when thawing is complete. Even though the model is only five days late in its prediction of the thaw date, the rapid rise in temperature that follows complete thawing results in average errors exceeding 5°C. It should be noted that 1) the temperature error caused by inaccurate prediction of the thaw date is not propagated indefinitely—errors return to very low levels by October, and 2) maximum errors occur during summer, when battery operation is not critical and battery temperatures are reasonably high.

5. DISCUSSION

The model is sufficiently accurate for use in simulation: it is unlikely that, given the uncertainties in battery modelling, the errors of this model will be the factor limiting accuracy in a simulation of a stand-alone system.

The model is considerably more accurate than the ad hoc methods typically used by simulation programs. For the entire monitored period, Table 4 compares the model with 1) setting the battery temperature equal to the ambient temperature, and 2) setting it equal to the average temperature over the month. The comparison is for the site without PCM; with PCM, the errors for these ad hoc methods will be much larger, since when the PCM is freezing a large temperature difference between the inside and outside of the enclosure is maintained.

	MBE	RMSE	Max error
Model, Batt. 100 % Eff.	-4.1	4.3	-7.0
Model, Batt. Ineff.	-0.8	1.4	-3.4
$T_b = T_{amb}$	-4.3	8.4	-24.5
$T_b = T_{amb\ over\ month}$	-4.3	6.1	-15.5

Table 5 Annual Error (°C): Model Compared with Ad Hoc Methods

It is instructive that the mean bias errors are all roughly the same except for that of the model accounting for heating due to battery inefficiencies. This makes sense: were there no heat generation in the enclosure, the long-term average of the battery temperature would equal the long-term average of the ambient temperature. The negative of the MBE is, therefore, the average amount by which heating due to battery inefficiencies raises the battery temperature.

In terms of absolute error, the MBE and RMSE for the ad hoc methods are not that large, and while much larger than the error of the model accounting for battery inefficiencies, they are comparable to that of the model not accounting for battery inefficiencies. The real problem is revealed by the "Max error" column, which lists the error of maximum magnitude. The ad hoc methods sometimes grossly over or underestimate the battery temperature. Since battery capacity is a function of battery temperature, these errors can lead to gross errors in simulation and sizing; for example, simulation could suggest that a PV system would function properly when, in fact, it would fail.

For an accurate simulation, the battery temperature needs to be known at all times, so that its effect on charge acceptance and efficiency can be taken into account. For rough sizing, however, just an estimate of the minimum battery temperature can be helpful: this dictates the minimum acceptable state-of-charge.

The models and ad hoc methods are compared on the basis of their predictions of the minimum battery temperature at the site without PCM in Table 5. The table also demonstrates how the error in the estimate of the minimum battery temperature would affect the sizing of the battery, assuming that some minimum level of usable battery capacity was necessary at all times. A battery with a specific gravity of 1.30 when fully charged is assumed, and the freezing of the electrolyte is considered the only limit on discharge capacity.

	T_{min} (°C)	Error in Battery Sizing
Monitored	-22.0	Na
Model, Batt. 100 % Eff.	-25.7	+13%
Model, Batt. Ineff.	-22.1	0%
$T_b = T_{amb}$	-37.2	+51%
$T_b = T_{amb\ over\ month}$	-18.1	-14%
$T_b = T_{amb\ over\ month,\ climatic\ normals}$	-13.8	-28%

Table 6 Comparison of Predicted Minimum Battery Temperature and Effect on Battery Sizing

It is impressive that the model accounting for battery inefficiencies predicts the minimum battery temperature to within the limits on the accuracy of the monitoring system; there would have been no appreciable error in the battery sizing with this model. In contrast, assuming that the battery temperature was equal to the ambient temperature would result in a battery 51% too large.

Surprisingly, the model not accounting for battery inefficiencies is not significantly more accurate than using the average ambient temperature over the month to estimate battery temperature. This does not necessarily mean that the average monthly temperature is a good estimator of minimum battery temperature, however, because 1) the model's estimate was conservative while the ad hoc method undersized the battery, 2) in the real world, the ambient air temperature over the month would probably be estimated from the climate normals (i.e., based on historical tendencies), resulting in a 28% error as shown in the final row of Table 6. This underlines the importance of methods for synthesizing temperature data from weather statistics, as discussed below.

The accuracy of the ad hoc methods for this particular case is a poor indication of how they perform in general. The degree to which variation in the ambient temperature is smoothed is dictated by τ. The amount by which battery heating due to inefficiencies shifts battery temperature above the long term average is influenced by P and the insulation in the enclosure. These variables will differ from battery bank to battery bank, affecting the accuracy of the ad hoc methods. For example, the ambient air temperature could be a good estimate of battery temperature when τ is very small and the average temperature over the month could work reasonably well when P is small. In contrast, because the model explicitly incorporates these variables, its accuracy should remain high over a wide range of cases.

The performance of the enclosure with PCM is interesting of itself. Despite the severity of the winter during which it was tested—ambient temperatures reached –37°C—the enclosure with PCM kept the battery above –5°C at all times. This demonstrates the technical feasibility of using PCM to establish a "floor" temperature below which the battery will not fall, eliminating uncertainty about the minimum battery temperature. Furthermore, although the enclosure was extremely well insulated, the summer temperature did not rise above 22°C, and stayed below 10 °C until July. This combination of cool summer and reasonable winter temperatures should lead to improvements in battery performance, reliability, and lifetime.

The above model is not the solution for all modelling software. The different requirements of sizing and simulation packages as well as the limited weather data actually available pose three problems:

1) Given a time series of weather data on, say, an hourly basis, model the evolution of the battery temperature for a specified system. This is of use to simulation packages.
2) Given some weather statistics (typically monthly means and variances of temperature and insolation), predict the minimum battery temperature. This is of use to sizing software using a monthly time-step.
3) Given some weather statistics (typically monthly means and variances of temperature), synthesize realistically distributed and correlated hourly temperature data. This is of use to simulation packages; it permits simulation when hourly weather data is not available.

The latter two problems require the techniques of time-series analysis and are outside the scope of this paper. They are, nevertheless, extremely important problems.

Two complications in all of the three above problems are 1) the correlation of insolation and ambient temperature and 2) the heat generated by a battery during charging links battery temperature to insolation. Sizing would be simplified if low temperatures were perfectly correlated with low insolation levels. They are not; for example, in most of Canada minimum ambient temperatures occur in January or February, but minimum insolation occurs in December.

6. CONCLUSIONS

Lead-acid battery operation is strongly affected by battery temperature; this is especially true at cold temperatures. Despite this, most sizing and simulation packages do not incorporate accurate models for battery temperature. This can result in incorrect sizing of the battery, which leads to system failure or high system costs. In addition, existing simulations are incapable of determining the utility of insulated enclosures and phase change materials.

Given a time series of ambient temperature data and current flow to the battery, the battery temperature can be modelled to within several °C. In contrast, the ad hoc methods currently in use are quite inaccurate, showing maximum errors of 15 to 25°C in the one case examined. Furthermore, the accuracy of the ad hoc methods will vary depending on the battery, battery enclosure, load, and PV array, whereas the model accounts for these factors and will be accurate for a wide range of applications.

To accurately model battery temperature, the heat generated during battery charging and discharging must be

accounted for, especially when the battery enclosure is well-insulated and the heat generated due to charge and discharge is large.

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